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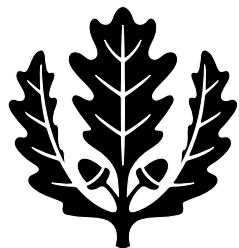
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**The Effects of Trade Orientation and Human Capital on Total
Factor Productivity**

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Abstract

We study the effects of trade orientation and human capital on total factor productivity for a pooled cross-section, time-series sample of developed and developing countries. We first estimate total factor productivity from a parsimonious specification of the aggregate production function involving output per worker, capital per worker, and the labor force, both with and without the stock of human capital. Then we consider a number of potential determinants of total factor productivity growth including several measures of trade orientation as well as a measure of human capital. We find that a high degree of openness benefits total factor productivity and that human capital contributes to total factor productivity only after our measure of openness passes some threshold level. Before that threshold, increases in human capital actually depress total factor productivity. Finally, we also consider the issue of convergence of real GDP per worker and total factor productivity, finding more evidence of convergence for the latter than for the former.

1. Introduction

Growth theory, an area of study with a long and distinguished history, drifted out of the mainstream of economics with the emergence of concern about short-run stabilization issues. This trend has reversed as growth theory has moved back onto the stage of macroeconomic analysis. This reemergence occurred partly in response to the provision of comparable cross-country data by Summers and Heston but also in recognition of the fact that small changes in economic growth, if sustainable, lead to huge long-run effects. In other words, the welfare implications from understanding and possibly affecting economic growth swamp the gains, if any, from short-run stabilization programs.

One piece to the growth puzzle, and our major focus, is the role of external factors in economic growth. Trade and exchange rate regimes interact with other economic and non-economic factors to affect changes in real per capita income.¹ Larger trade implies greater openness that facilitates the economy's adoption of more efficient techniques of production, leading to faster growth of total factor productivity and, hence, real per capita income. The expansion of exports relaxes the foreign exchange constraint and allows for larger imports of key inputs in the production process. Finally, improvements in the terms of trade can exogenously increase output.

The reemergence of growth theory as an important topic of investigation has also refocused much of the debate toward how public policy can affect economic growth. The standard neo-classical growth models [i.e., the descriptive growth model of Solow (1956), the optimal growth model of Ramsey (1928), or the overlapping generations model of Samuelson (1958), as well as their descendants] have been challenged by the literature on endogenous growth. The neo-classical paradigm considers technological

¹ Mankiw (1995) and Ventura (1997) argue that the process of equalization of factor prices internationally improves the substitutability of capital and labor, thus, improving growth prospects.

change as an exogenous process whereas the endogenous growth literature makes this process endogenous, looking for possible driving forces.

Mankiw (1995) provides a recent, clearly articulated discussion of the practical empirical problems associated with the neo-classical approach along with a proposed solution. Mankiw (1995) avers that the neo-classical model has problems addressing at least three empirical regularities. To wit, the model cannot explain the observed differences in real income per capita across countries, the observed rate of convergence across countries, or the observed differences in real rates of return across countries. He modifies one parameter, the returns to capital, by defining capital to include both physical and human capital, and argues that this one change goes a long way toward allowing the neo-classical model to explain these three empirical regularities.²

Economists, at least since the time of Solow (1957), explain output growth in terms of the accumulation of factor inputs and of the growth of total factor productivity. The explosion of growth accounting regressions in the last decade or so has commonly searched for additional determinants of growth beyond the basic factors of production. In effect, these studies treat all possible determinants of output growth as inputs. Such an approach may be conceptually inaccurate, since many of the included determinants may have only indirect effects on output. Rather, these determinants affect the efficiency of the real inputs, physical capital, labor, and possibly human capital. Consequently, these additional determinants of output growth directly affect total factor productivity.

An important assumption in Mankiw's (1995) analysis of neo-classical growth theory, for example, is that human capital enters the production function along with labor and physical capital. An alternative view might argue that physical capital

² Romer (1995), a leading proponent of endogenous growth theory, disagrees strongly with Mankiw's conclusion that changing the capital share rescues the neo-classical model.

contains mixes of different vintages and that human capital contains mixes of different skills. Measures of human capital attempt to reflect the skill mix within a country, recognizing that such measures are typically crude indices of the average level of education or training. To our knowledge, no comparable measure of the technology base that reflects the mix of capital vintages exists. Moreover, we can argue that the vintage mix of capital and the skill mix of labor reflect the existing stock of technological advantage extant within a given country's economy. As such, we should logically look for the effect of human capital on total factor productivity growth rather than include it directly into the production function. An agnostic approach, which we adopt, examines both possibilities for the effect of human capital on the growth process.

Our analysis evolves in two steps. First, we calculate two measures of total factor productivity derived from production function specifications that exclude and include our measure of human capital as an input. Second, we search for significant determinants of total factor productivity, especially measures of trade and openness. While the existing literature has identified total factor productivity to be large and significant, much less work exists that searches for the determinants of total factor productivity. We add some depth to this latter discussion.

The neo-classical models also imply some form of convergence in real income per capita. Absolute convergence tests whether real income per capita converges to a steady state value, irrespective of other conditions within a given country. Conditional convergence, on the other hand, allows each country to have a different level of real income per capita toward which it is converging. Differences in steady-state values of real per capita income across countries reflect differences in such factors as the saving rate, the population growth rate, and so on. We test for convergence both in real income per capita and in total factor productivity.

We can state our basic findings simply. First, human capital has a significant effect on output when it is included as a factor of production. The incorporation of

human capital in the production function lowers the elasticity of output with respect to labor when compared to the production function without human capital as an input. The elasticity of output with respect to physical capital remains essentially unaltered by the introduction of human capital as an input.

Second, we find that one measure of the openness of an economy [the ratio of exports to gross domestic product (GDP)] has a significant positive effect on total factor productivity. Further, human capital interacts significantly with openness in this case to affect total factor productivity. Human capital has a positive effect on total factor productivity only if openness exceeds a threshold value. If openness falls below this threshold value, then human capital has a negative effect on total factor productivity.

Finally, we find evidence of absolute convergence in real GDP per capita only for the OECD countries in our sample, a finding consistent with the existing literature. But we also discover evidence of absolute convergence of total factor productivity for the whole sample of developed and developing countries.³ That is, the convergence of total factor productivity does not hinge on the relative position of a given country, as is the case for real GDP per capita (i.e., conditional convergence).

Our paper progresses as follows. In the next section, we estimate parsimonious production functions and determine the levels of total factor productivity under two specifications -- one with and one without the stock of human capital as an input. In section 3, we report the results of tests for convergence of real GDP per capita and of total factor productivity. We search for various determinants of total factor productivity in section 4. Finally, we conclude in section 5.

2. Estimates of the Production Function and Total Factor Productivity

³ Despite evidence of absolute convergence, we do not detect much support for a narrowing of the spread of income distribution over time, except for the sub-sample of high-income countries.

The measurement of total factor productivity requires the estimation of a production function from which we derive the total factor productivity measure. To keep the analysis simple, we adopt, as a first approximation, the Cobb-Douglas production function. Thus, our two production functions, one excluding and one including the stock of human capital, are expressed as follows:

$$(1) \quad Y = A K^a L^b, \quad 0 < a < 1 \text{ and } 0 < b < 1, \text{ and}$$

$$(2) \quad Y = A K^a H^g L^b, \quad 0 < a < 1, 0 < g < 1, \text{ and } 0 < b < 1,$$

where Y equals real GDP, K equals the total physical capital stock, L equals the number of workers (labor force), H equals our measure of human capital, and A equals an index of total factor productivity. We allow for the possibility of non-constant returns to scale by not restricting $(a + b)$ or $(a + b + g)$ to equal one.

Dividing equations (1) and (2) by the labor force (L) expresses output, the physical capital stock, and the human capital stock on a per worker basis. That is,

$$(3) \quad y = A k^a L^{a+b-1}, \text{ and}$$

$$(4) \quad y = A k^a h^g L^{a+b+g-1},$$

where y equals real GDP per worker, k equals the per worker stock of physical capital, and h equals the per worker stock of human capital. These production functions display increasing, constant, or decreasing returns to scale as $(a + b)$ or $(a + b + g)$ are greater than, equal to, or less than one, respectively.

Rewriting equations (3) and (4) in natural logarithms yields the following:

$$(5) \quad \ln y = \ln A + a \ln k + (a + b - 1) \ln L, \text{ and}$$

$$(6) \quad \ln y = \ln A + a \ln k + g \ln h + (a + b + g - 1) \ln L.$$

Thus, the tests for constant returns to scale involve whether the coefficient of $\ln L$ equals zero.

The inclusion of human capital as an input in the production function is controversial. Mankiw, Romer, and Weil (1992) advocate such an approach on both theoretical and empirical grounds, and obtain a better fit after including human capital

in their cross-section regressions. Islam (1995), using panel regressions, finds that human capital does not contribute significantly to explaining output in the Mankiw-Romer-Weil specification. He does suggest that human capital significantly affects total factor productivity, but leaves a more definitive statement for future research.

Benhabib and Spiegel (1994) also incorporate human capital into a logarithmic-differenced (i.e., growth-rate) estimation of the production function. They discover insignificant or negative coefficients for the human capital variable (i.e., the growth rate of human capital). This finding leads them to consider more complex paths (i.e., through interaction terms) whereby human capital affects growth. They conclude that human capital does not enter the production function as an input, but rather influences growth through its effect on total factor productivity.

We use, as does Islam (1995), panel data to estimate the production function. Our data cover the 1960 to 1989 time period (1959 to 1989 for any growth rate) for a sample of 83 countries. The following regions are represented in our data set : Africa (19 countries), Caribbean, Central America, and North America (13), South America (11), Asia (16), Europe (20), and Oceania (4). The Data Appendix, Table A, lists the countries included in our sample. Data availability limited the country sample. Our panel combines data in five-year blocks as follows: 1960-64, 1965-69, 1970-74, 1975-79, 1980-84, and 1985-89. Usually, the data are averages of the five years in each block.

The data for estimating the production function come largely from the Summers and Heston Penn World Table 5.6 (PWT5.6). The output measure is real GDP per worker (1985 international prices) averaged over five-year blocks. The labor force is derived from the reported data on real GDP per capita, real GDP per worker, and population. The labor force is also averaged over five-year blocks. The physical capital stock per worker was not available for all years in all countries. Thus, to keep from losing too many countries in the panel, we estimated the capital stock from investment flow data and some benchmark stocks of physical capital. (See the Data Appendix for

details.) Finally, the stock of human capital is based on the average years of schooling per adult reported by NBER/Barro and Lee (1994). (See the Appendix for details.) Due to data availability, we measure the stock of human capital at the beginning of each five-year period rather than an average over the period (i.e., 1960 for the 1960-64 time period).

Our data encompasses 498 observations (83 countries and 6 time blocks). Our estimating equations emerge by adding random errors to equations (5) and (6). These error terms incorporate the effects of omitted variables. Classical regression analysis assumes that the omitted variables are independent of the included right-hand-side variables and are independently, identically distributed.

When using panel data, however, we can further classify the omitted variables into three groups -- country-varying time-invariant, time-varying country-invariant, and country- and time-varying variables.⁴ The country-varying time-invariant variables differ across countries, but are constant within a country over time. Examples include a country's geography, location, or climate. The time-varying country-invariant variables differ over time, but are constant at a point in time across countries. Examples here include worldwide business cycle events or technological shocks. Finally, country- and time-varying variables differ across both countries and time.

The estimation of equations (5) and (6) without consideration of possible country-specific or time-specific effects can generate misleading results for ordinary-least-squares regressions. Hsiao (1986) provides examples of misleading results. Problems emerge when either the unobservable country-specific or time-specific variables correlate with the included right-hand-side variables. Two alternative, but related, procedures exist for addressing these problems -- fixed-effect and random-effect models. We restrict our attention to fixed-effect estimation since the random-

⁴ Our discussion of panel estimation relies heavily on Hsiao (1986) and Greene (1990).

effects estimation requires that the omitted variables are uncorrelated with the included right-hand-side variables -- an unrealistic assumption in the context of our model.

Suppose that the problem is the omission of country-specific variables that correlate with the included right-hand-side variables. A solution to this problem adjusts the dependent and independent variables by subtracting the mean of each variable over time.⁵ Since the unobserved country-specific variables and the intercept do not change over time, the subtraction of their respective means over time drops these variables out of the regression equations. If this is the only problem with equations (5) and (6), then the regression adjusted for means across time provides unbiased and consistent estimates of the coefficients. Without adjustment, ordinary-least-squares produces biased and inconsistent estimates.

If the problem is time-specific variables that are correlated with the included right-hand-side variables, a similar solution adjusts the dependent and independent variables by subtracting the mean of each variable over countries. Since each country faces the same time-specific effects, subtracting the mean over countries drops the intercept and the time-specific effects out of the revised regression equations. Once again, the revised regression equations provide unbiased and consistent estimates.

Of course, it is possible that both country-and time-specific effects correlate with the included right-hand-side variables. In this case, we can adjust for the means over countries and time. We adopt this last approach and consider fixed effects over countries and time. Our problem, however, has few elements in the time dimension. Thus, rather than adjusting the data as deviations from the mean across countries, we include time-specific dummy variables (i.e., six dummy variables for the six time

⁵ An alternative procedure estimates a first-differenced regression. Lagging equations (5) and (6) by one period and subtracting the lagged equation from the unlagged counterpart causes the intercept and the country-specific terms to drop out. Benhabib and Spiegel (1994) estimate a logarithmic differenced production function which matches the fixed-effect estimation over the two time periods in their sample.

periods). We still adjust the data as deviations from the means over time within each country rather than include country-specific dummy variables, which would necessitate 83 additional variables.

The estimated equations are as follows:⁶

$$(7) \quad \ln y = \ln A + a \ln k + (a + b - 1) \ln L + \sum_{i=1}^6 q_i \text{time}_i + e_t \quad \text{and}$$

$$(8) \quad \ln y = \ln A + a \ln k + g \ln h + (a + b + g - 1) \ln L + \sum_{i=1}^6 q_i \text{time}_i + e_t,$$

where time_i ($i = 1, \dots, 6$) represent the time dummy variables and the variables for each country measure deviations from their country means over time. We then calculate the country-specific fixed effects of intercepts (cint_j) as follows:

$$(9) \quad \text{cint}_j = \overline{\ln y}_j - \hat{a} \overline{\ln k}_j - \hat{d}_1 \overline{\ln L}_j \quad \text{and}$$

$$(10) \quad \text{cint}_j = \overline{\ln y}_j - \hat{a} \overline{\ln k}_j - \hat{g} \overline{\ln h}_j - \hat{d}_2 \overline{\ln L}_j,$$

where “-” over a variable means the mean of that variable, “^” over a parameter means the estimate of that parameter, $\hat{d}_1 = (a + b - 1)$, $\hat{d}_2 = (a + b + g - 1)$, and $j = \{1, 2, 3, \dots, 83\}$ is the index across countries. Note that the time-specific fixed effects appear directly as the respective coefficients of the time dummy variables.

Table 1 reports the estimates of equations (7) and (8) as well as two modifications of equation (7). Column one gives the estimate of equation (7). The coefficient of $\ln L$ (i.e., -0.0988), although only significant at the 20-percent level, indicates that the production function exhibits slightly decreasing returns to scale. The coefficient of $\ln k$ assigns a value of 0.4756 to the elasticity of output with respect to the physical capital stock. These two coefficients combine to generate the implied elasticity of output with respect to the labor force of 0.4256. Thus, after accounting for country-

⁶ The estimation of an aggregate production function confronts the researcher with numerous problems. One major concern is the possible endogeneity of physical and human capital, since these factors are accumulated over time. Benhabib and Spiegel (1994) examine this issue and conclude that the coefficients of physical and human capital probably over-estimate their effects while the coefficient of labor probably under-estimate its effect. The reader needs to keep these potential biases in mind when interpreting our findings.

and time-specific effects, the output elasticities with respect to labor and physical capital sum to a value of 0.9012.

Column two in Table 1 reports the estimates of equation (8), where our measure of the stock of human capital per worker in logarithmic form enters the production function.⁷ Now, the output elasticity with respect to human capital equals 0.1136, which is significantly different from zero at the 10-percent level. The output elasticity with respect to physical capital remains essentially unchanged from the specification without human capital at 0.4712. The combined elasticity of output with respect to physical and human capital totals 0.5848, a result not too far from the findings of Mankiw, Romer, and Weil (1992). The implied elasticity of output with respect to the labor force falls to 0.2769, suggesting that the coefficient of labor in the specification without human capital captures much of the influence of human capital. In sum, our results on the effect of human capital in the production function support the findings of Mankiw, Romer, and Weil (1992) and differ from those of Islam (1995) and Benhabib and Spiegel (1994).

An alternative method of incorporating human capital into estimates of the production function allows for the interaction of human capital with either physical capital or the labor force.⁸ That is, changes in human capital affect either the elasticity of output with respect to physical capital or the labor force. Column three of Table 1 reports the results of interacting the stock of human capital with the stock of physical capital per worker while column four, human capital and the labor force. The elasticity of output with respect to physical capital is significantly affected by the stock of human

⁷In fact, we measure the stock of human capital as the average years of schooling per adult. We assume that the variable provides a good proxy for the average years of schooling per worker.

⁸ To calculate the total stock of human capital, we multiply our measure of human capital (i.e., average years of schooling per worker) times the number of workers to get the average years of schooling in the labor force.

capital; the elasticity of output with respect to labor is not. So, once again, we find evidence suggesting a link between human and physical capital rather than human capital and the labor force.

The time-specific dummy variables tell a consistent story. That is, total factor productivity increases over each five-year time span, beginning in 1960-64 and ending in 1975-79. The last two time spans -- 1980-84 and 1985-89 -- suggest a stagnation in total factor productivity growth.

We employ the estimates of equations (7) and (8) (i.e., columns one and two in Table 1) to produce total factor productivity estimates for each country across the six time blocks. Table A in the Appendix reports the ranking of the 83 countries for our two different estimates of total factor productivity averaged across the six time blocks. These two sets of rankings possess a rank correlation of 0.9761, indicating a consistent pattern of country rankings across the two different estimates of total factor productivity. Moreover, the correlation between our two measures of total factor productivity and real GDP per worker equals 0.68 and 0.60 for the measures that exclude and include human capital in the production function, respectively.

3. Convergence Tests

A large literature tests for the convergence of real income per capita, beginning with Baumol (1986) and extending through Barro and Sala-i-Martin (1995), and Mankiw, Romer, and Weil (1992). The *Economic Journal* (1996) published a symposium discussing the "Controversy on the Convergence and Divergence of Growth Rates." In this symposium, Sala-i-Martin (1996) defends the traditional cross-section regression method of investigating convergence. Quah (1996) presents a strong critique of this traditional approach, arguing in favor of examining the distribution of real income per capita over time. In another critique, Bernard and Jones (1996) argue that the traditional approach over-stresses the role of capital accumulation and ignores or under-

emphasizes the importance of technological diffusion in understanding convergence or divergence issues.

We test for the convergence of real GDP per worker as well as for the convergence of total factor productivity. The tests for convergence of total factor productivity provide some new insight as to the spread, adoption, and convergence of technological advances. As such, our tests offer some insight into the questions raised by Bernard and Jones (1996). Finally, our tests also may shed some light on the argument about whether technology is a public or a private good. That is, if technology is a public good that can speedily transit international boundaries, then we should find convergence of total factor productivity.

The neo-classical growth models each imply convergence of real income per worker. The various empirical tests for convergence fall under two categories -- tests of unconditional (absolute) or conditional convergence. Unconditional convergence means that each country moves toward the same steady-state real GDP per worker. Conditional convergence suggests that each country possesses its own steady state real GDP per worker to which it is converging. The steady state in each country is conditioned on the state of its economy. For example, the Solow (1956) growth model implies that the steady-state real GDP per worker across countries depends on the saving and population growth rates in each country.

Two types of convergence exist in the literature -- β -convergence and σ -convergence. Convergence of the β -type considers whether the growth rates of countries exhibit a negative correlation with the level of real GDP per worker. That is, β -convergence implies that countries with low real GDP per worker possess faster growth rates than countries with high real GDP per worker. Convergence of the σ -type considers whether the dispersion of real GDP per worker diminishes over time. That is, σ -convergence implies that the distribution of real GDP per worker across countries gets tighter over time, thus reducing some measure of dispersion.

Tests for β -convergence regress the growth rate of real GDP per worker onto the initial value of real GDP per worker to test for absolute convergence and onto the initial value of real GDP per worker and other control variables (e.g., investment to GDP) to test for conditional convergence. Tests for σ -convergence consider the movement of a measure of dispersion of real GDP per worker over time. As such, σ -convergence must of necessity measure absolute convergence. For example, if all countries have the identical level of steady-state real GDP per worker, then σ -convergence implies that the measure of dispersion approaches zero over time. On the other hand, if all countries have different levels of steady-state real GDP per worker, then the dispersion of steady-state real GDP per worker must represent the steady-state level of dispersion to which real GDP per worker is converging. That is, σ -convergence in this case implies that the measure of dispersion approaches the steady-state dispersion of real GDP per worker. As a result, if the measure of dispersion is below its steady-state level, then convergence implies a rising, not falling, measure of dispersion.

Empirical studies of β -convergence typically find evidence of absolute convergence only for samples of developed (OECD) countries. Samples that include both developing and developed countries or samples that include only developing countries typically do not exhibit evidence of absolute convergence. Evidence of conditional convergence, however, does frequently emerge in samples that include both developing and developed countries. Empirical tests of σ -convergence are much fewer (e.g., Friedman 1992 and Sala-i-Martin 1996). Nonetheless, they tell a similar story as that associated with absolute convergence, which we might expect.⁹

⁹ Quah (1996) argues that this increased emphasis on σ -convergence still misses the point of whether “... poor countries are catching up with rich countries” (p. 1053). Quah (1996) also provides a discussion of his alternative views on economic growth and convergence.

We first test for absolute β -convergence in two ways -- a cross-section test and a pooled cross-section, time-series test. All regressions of absolute convergence have the following form:

$$(11) \quad g_{yt} = \ln y_t - \ln y_{t-1} = \mathbf{a} + \mathbf{b}_y \ln y_{t-1} + \mathbf{e}_{yt},$$

where g_{yt} is the growth rate of real GDP per worker from $(t-1)$ to t (approximated by the logarithmic difference), y_{t-1} is the level of real GDP per worker in $(t-1)$, and \mathbf{e}_{yt} is the random error. We calculate the growth rates and levels of real GDP per worker using the average levels of real GDP per worker in each time block of five years. That is, we have average levels of real GDP per worker in 1960-64, 1965-69, ... , and 1985-89 for each country. The growth rate for the cross-section test calculates g_{yt} as the logarithmic difference between real GDP per worker in 1985-89 and 1960-64 divided by 25 and the lagged logarithm of real GDP per worker is for 1960-64 (i.e., the initial time period in the cross-section test).¹⁰ The growth rates for the pooled cross-section, time-series tests calculate g_{yt} as the logarithmic difference of real GDP per worker between 1965-69 and 1960-64, between 1970-74 and 1965-69, ... , and between 1985-89 and 1980-84, each divided by 5; and the corresponding lagged logarithms of real GDP per worker are for 1960-64, 1965-69, ... , and 1980-84.¹¹

Similar regressions are performed where total factor productivity replaces real GDP per worker. That is, the regressions for β -convergence of total factor productivity have the following form:

$$(12) \quad g_{tftp} = \ln tfp_t - \ln tfp_{t-1} = \mathbf{a} + \mathbf{b}_{tftp} \ln tfp_{t-1} + \mathbf{e}_{tftp},$$

¹⁰ We divide the logarithmic difference between real GDP per worker in 1985-89 and 1960-64 by 25 to approximate the annual growth rate between 1962 and 1987, the two mid-points of the 1960-64 and 1985-89 periods, respectively.

¹¹ Now, the logarithmic difference between real GDP per worker in 1965-69 and 1960-64 implies a five-year difference between the mid-points of the two five-year time blocks (i.e., 1962 and 1967, respectively).

where tfp equals total factor productivity. The same construction of variables for the growth rates and lagged logarithms hold as described for real GDP per worker in the prior paragraph.¹²

Finally, the pooled cross-section, time-series regressions were implemented using the fixed-effect technique that we applied to the estimation of the production functions in the previous section. All variables in each country were constructed as deviations from the means over time. And we included time dummy variables to capture the time fixed effects in our pooled cross-section, time-series regressions. Since the regressions involve growth rates, we lose 83 observations (one for each country) in our pooled cross-section, time-series regressions.

The results of our β -convergence tests appear in the top part of Table 2. Several items deserve mention. The pure cross-section test for β -convergence of real GDP per worker (row 1 in Table 2) tells a story consistent with the existing literature. That is, no evidence exists of β -convergence for the whole sample of 83 countries or for the two sub-samples of the 22 low-income countries or the 38 middle-income countries.¹³ Evidence exists of β -convergence at the 10-percent level for the high-income countries only.

¹² We conduct tests of equation (12) for our two measures of total factor productivity -- measures that exclude and include the stock of human capital in the first-stage production function estimation.

¹³ We divided our sample into low-, middle-, and high-income countries based on real GDP per worker in the 1960-64 period. The World Bank divides countries into low-, middle-, and high-income countries based on real GDP per capita. Using a number in the range of 2 to 2.5 to measure the ratio of population to the number of workers, we convert these ranges into ranges based on real GDP per worker. Low-income countries had an average income for 1960-64 below \$3,000 per worker; middle-income countries, between \$3,000 and \$10,000 per worker; and high-income countries, above \$10,000 per worker.

A slightly different story emerges for the cross-section β -convergence tests for total factor productivity (row 2 in Table 2).¹⁴ Here, evidence of β -convergence of total factor productivity exists for the full sample of countries as well as for each sub-sample of low-, middle-, and high-income countries. The evidence for β -convergence strengthens as the focus moves from low-income countries (significant at the 20-percent level) to middle-income countries (significant at the 10-percent level) to high-income countries (significant at the 1-percent level). In addition, the β coefficient is negative and significant at the 1-percent level for the full sample.

What do these results tell us? To the extent that our measure of total factor productivity captures the technological character of the production process, these convergence findings suggest more evidence of convergence of technology than real GDP per worker. Of course, as noted above, the neoclassical growth models do not imply unconditional convergence of real GDP per worker, since differences in economic conditions (e.g., savings rates and population growth rates) lead to different steady states. No similar argument, to our knowledge, applies to the convergence of technology. Rather convergence in total factor productivity associates with the view that technology is a public good while non-convergence associates with technology as a private good.¹⁵ As a result, the stronger findings for the convergence of technology may indicate that the public-good nature of technology dominates any private-good dimension.

¹⁴ We report only the results for the total factor productivity measure that excludes the stock of human capital in the first-stage production function estimation. The results for our second measure of total factor productivity mirrors closely the reported results. These additional results are available on request.

¹⁵ In fact, non-convergence can associate with technology that is a public good, if the high-income innovative countries discover new technology at a rate faster than the diffusion and adoption of old technology by the poorer countries.

We also test for β -convergence using our pooled cross-section, time-series data set.¹⁶ In general, the findings of β -convergence are strengthened when compared to the single cross-section results reported in the previous paragraphs. The panel tests for β -convergence of real GDP per worker (row 3 in Table 2) indicate significant evidence of convergence for the full sample at the 1-percent level unlike the insignificant findings for the single cross-section. Similarly, we now uncover evidence of β -convergence of real GDP per worker for the low-, middle-, and high-income groups at the 20-, 1-, and 1-percent levels, respectively.

How might such differences in findings emerge? First, the panel data tests allow for each country's growth rate to respond to changes in its level of real GDP per worker accomplished over prior five-year periods. For example, a country with low income may experience rapid growth in accordance with the convergence hypothesis. To the extent that this country closes the gap on high-income countries, then the convergence hypothesis suggests that its growth rate should slow. The panel data estimates facilitates such scenarios whereas the single cross-section regression rules them out. That is, in single cross-section regression, a country's growth rate averaged over the entire period is linked to its initial real GDP per worker.

Second, the panel data approach controls for country and time fixed effects. To the extent that this method accommodates differences across countries and time, the test actually transforms into a test of conditional convergence, conditional on those fixed effects across countries and time. As such, finding more evidence of convergence in the panel estimation appears reasonable.

¹⁶ Islam (1995) provides similar tests for β -convergence using panel data constructed with time periods of five-year duration. Miller (1996) and Miller and Russek (1997) test for β -convergence using panel data where each year is a separate entry in the panel. Miller and Russek (1996) test for β -convergence across the states in the United States using panel data also where each year is a separate entry in the panel.

Similar results emerge for the β -convergence tests for total factor productivity (row 4 of Table 2). The panel results indicate more support for convergence than found in the single cross-section results with one exception. Now, the panel results suggest weaker evidence of convergence in total factor productivity for the high-income countries. That is, all results are significant at the 1-percent level except for the high-income countries where the significance level is 20-percent. Moreover, the β -convergence test is not significant for the high-income countries when we use the other measure of total factor productivity (not reported).

The weak or no finding for convergence of total factor productivity for the panel data regressions in the high-income countries may reflect to some extent the arguments of Bernard and Jones (1996). That is, if we argue that technological advance occurs in the high-income countries as a rule and that technology flows from the technological innovators to the other countries, then we may expect convergence in total factor productivity among those countries who are adopting existing technology, but no convergence among the innovators. Our findings are consistent with this story.

Our results for σ -convergence appear in the bottom part of Table 2. Our measure of σ -convergence is the standard deviation of real GDP per worker or total factor productivity over the five-year sub-periods. Once again, several observations deserve mention. The σ -convergence of real GDP per worker provides little evidence of convergence. The standard deviation tends to increase over the six five-year sub-periods for the full sample of countries as well as for the low-income and middle-income samples. We do observe a declining standard deviation for the high-income country sample. But even here, the standard deviation increases in the 1980s. In addition, the upward movement in the standard deviation of real GDP per worker for the whole sample and for the samples of low-income and middle-income countries also rises more dramatically during the 1980s.

The σ -convergence of total factor productivity deviates somewhat from the findings for real GDP per worker.¹⁷ Now, the standard deviation of total factor productivity declines gradually for the full sample to 1980-84 before rising in 1985-89. Also, the decline in this standard deviation is monotonic for the high-income countries. Low-income countries saw the standard deviation of total factor productivity falling through 1975-79 and increasing thereafter while the standard deviation for the middle-income countries was fairly stable until increasing in the 1980s.

Quah (1996) argues strenuously that the convergence debate misses the point -- that is, the churning of the income distribution among countries over time. He suggests that evidence exists of convergence toward twin peaks or of convergence clubs. To examine this issue, we arrange countries by income into 8 groups and plot the number of countries in each group versus income in each time period.¹⁸ This provides a rough-and-ready method of looking for twin peaks or convergence clubs. We observe a single-peaked distribution in 1960-64 that becomes triple-peaked in 1965-69 at low-, middle-, and high-income levels. The picture reverts to a single peak in 1970-74, 1975-79, and 1980-84 before shifting to twin peaks at reasonably high income levels in 1985-89. Thus, multiple clustering of countries at different parts of the income scale occurs on some occasions, but the clustering is by no means systematic.¹⁹

In sum, our analysis of convergence uncovers few surprises. Several new observations do emerge, however. We find stronger evidence of convergence of total factor productivity than of real GDP per worker. In addition, we discover strong

¹⁷ Although unreported, similar findings emerge for our other measure of total factor productivity that includes the stock of human capital in the first-stage production function estimation. These results are available on request.

¹⁸ The income ranges expressed in the logarithm of real GDP per worker extend from 6.5 to 10.5 in increments of 0.5.

¹⁹ Quah (1996) provides a thorough discussion of the twin peaks or convergence clubs ideas. Charts of the distribution of countries by income is available to interested readers on request.

evidence of convergence of total factor productivity for low- and middle-income countries, but weak evidence for high-income countries.

4. Determinants of Total Factor Productivity

This section studies the role of trade-related variables and other factors in influencing total factor productivity. We derived two different measures of total factor productivity in section 2 based on estimated production functions that exclude and include our measure of the stock of human capital. Our estimating equation takes the following form:

$$(13) \quad \ln tfp = a_1 + a_2 \ln H + a_3 \ln x + a_4 \ln tot + a_5 \ln pd + a_6 \ln (1+p) \\ + a_7 \ln s_x + a_8 \ln s_{tot} + a_9 \ln s_{pd} + a_{10} \ln s_\pi \\ + \sum_{i=1}^6 a_{10+i} time_i + e,$$

where x equals the ratio of exports to GDP,²⁰ tot equals the terms of trade, pd equals local price deviation from purchasing power parity, p equals the inflation rate, and s_i equals the standard deviation of i ($= x, tot, pd, \text{ and } p$) over the five-year sub-periods. Details on the variables are contained in the Data Appendix.

We estimate equation (13) using the fixed-effect method where each variable in each country is measured as a deviation from its mean over time. In addition, we include time dummy variables to capture fixed effects over time. Table 3 reports the results of our estimates of equation (13). Columns 1 and 3 report the estimates of equation (13) where the dependent variable is the total factor productivity variable that excludes and includes the stock of human capital in the first-stage production function regressions, respectively.

Taken together, the trade variables tell a cumulative, consistent story. The export-to-GDP ratio has a significant positive effect at the 1-percent level. A more open economy, other things equal, associates with higher total factor productivity. The local

²⁰ We also examined regression results where we used imports plus exports to GDP rather than just exports to GDP. The export-to-GDP ratio performed better.

price deviations from purchasing power parity has a significant negative effect at the 5-percent level. Here, larger deviations from purchasing power parity associate with lower total factor productivity. To the extent that local deviations from purchasing power parity imply a more-restricted, less-open domestic economy, then the coefficient on this variable captures another aspect of the openness of the economy to trade, reinforcing our finding on the export-to-GDP ratio. The terms of trade variable has a positive effect, but it is only significant at the 20-percent level. So improvements in the terms of trade weakly associate with higher total factor productivity.

The inflation rate has a significant negative effect on total factor productivity at the 1-percent level. This finding that higher inflation associates with lower total factor productivity may offer an explanation for the observed empirical regularity between higher inflation and lower economic growth.²¹ That is, higher inflation leads to lower economic growth through inflation's effect on total factor productivity.

The standard deviation variables have, on average, much less significance in explaining total factor productivity. The one exception, the standard deviation of exports to GDP, has a significant negative effect at the 1-percent level. That is, the less variable and more stable the export-to-GDP ratio, the higher is total factor productivity.

In sum, a higher and more stable export-to-GDP ratio, a lower inflation rate, and less local price deviation from purchasing power parity associate with higher total factor productivity. At the margin, improving the terms of trade also may lead to higher total factor productivity.

We also note that the specification in equation (13) leads to a stock of human capital variable that is insignificant in column 1 and significant at the 20-percent level and negative in column 3. These results are consistent with the findings of many

²¹ While Levin and Renelt (1992) find that the effect of inflation on economic growth is fragile, they do find that it is consistently negative. Kormendi and Meguire (1985), Grier and Tullock (1989), and Miller and Russek (1997) report evidence of a negative effect of inflation on economic growth.

researchers. These researchers, however, generally examine the effect of human capital on growth rather than on total factor productivity. Islam (1995) and Benhabib and Spiegel (1994) suggest that human capital may affect growth indirectly through total factor productivity.

Finally, as we also observed in the production function estimations, a significant pattern emerges in the time fixed effects. Total factor productivity grows monotonically, other things constant, from 1960-64 through 1975-79. Then it levels off and/or falls somewhat in the 1980s.

Human Capital-Trade Openness Interaction

Another possible avenue through which human capital affects total factor productivity is its interaction with trade orientation.²² Greater openness fosters competition, encourages the use of modern technology, increases the demand for high-skilled labor, and promotes learning by doing.²³

Columns 2 and 4 in Table 3 add the interaction term of human capital and the export-to-GDP ratio. The coefficient of the interaction term is positive and significant at the 5- and 10-percent levels for the total factor productivity measure that excludes and includes the stock of human capital in the first-stage production function regressions, respectively. Clearly, the effect of the ratio of exports to GDP on total factor productivity remain significant and positive [i.e., both coefficients of $(\ln x)$ and $(\ln H \ln x)$ are positive]. Now, however, the effect of openness is leveraged by the stock of human capital -- more human capital implies a larger effect of openness on total factor productivity.

²² Grossman and Helpman (1991) suggest that increased trade orientation may interact with human capital to produce higher output growth. Benhabib and Spiegel (1994) interact human capital with other variables including technological progress.

²³ Leamer (1995), among many others, claims that increased foreign trade of the United States has led to an increase in the real wage of skilled workers and a corresponding reduction in the real wage of unskilled workers.

The effect of the stock of human capital on total factor productivity becomes conditioned on the level of exports to GDP. For low levels of openness (i.e., exports to GDP), the coefficient on the stock of human capital, which is negative, dominates the positive coefficient on the interaction between openness and human capital. For large levels of openness, this effect of human capital on total factor productivity reverses and becomes positive, since the interaction term dominates the isolated effect of human capital.

We can calculate the level of exports to GDP at which the total effect of the stock of human capital on total factor productivity reverses sign. For the regression results reported in column 2 of Table 3, this reversal occurs when exports to GDP reaches about 11 percent. The level rises to about 50 percent in the results reported in column 4. We note that the results reported in column 4 already incorporate the effect of the stock of human capital on total factor productivity through the inclusion of human capital in the first-stage production function estimation. Thus, the level of openness at which human capital begins to have a positive effect on total factor productivity rises significantly from 11 to 50 percent.

This finding possesses intuitive appeal. To wit, as noted previously, greater openness fosters competition, encourages the use of modern technology, increases the demand for high-skilled labor, and promotes learning by doing. Too little openness, therefore, does not allow a country to leverage its stock of human capital. In other words, the investment in human capital absent liberalization of the external sector may lead to the under-utilization of human capital.²⁴

²⁴ Upadhyay (1994, 1997) provides a theoretical discussion of (1) large education subsidies that cause a rapid human capital expansion at the cost of expanding physical capital, and (2) the effect of public-sector schemes to employ human capital, frequently for reasons of political economy rather than public goods, that we observe in many countries in Africa or Asia.

Finally, we also note that the inclusion of the human capital and openness interaction term does not have significant effects on the magnitudes, signs, and significance of the other variables in the total factor productivity regressions.

5. Conclusion

We study the effects of trade orientation and human capital on total factor productivity for a pooled cross-section, time-series sample of developed and developing countries. We first estimate total factor productivity from a parsimonious specification of the aggregate production function involving output per worker, capital per worker, and the labor force, both with and without the stock of human capital. We next consider the issue of unconditional convergence for real GDP per worker and for total factor productivity. Finally, we search for the possible determinants of total factor productivity, with special emphasis on variables reflecting trade orientation.

We find that opening the economy to trade benefits total factor productivity. We capture the opening of the economy to trade through increasing exports to GDP, improving the terms of trade, and reducing local deviations from purchasing power parity. Moreover, the stock of human capital contributes to total factor productivity only after our one measure of openness (i.e., exports to GDP) passes some threshold level. Before that threshold, increases in human capital actually depress total factor productivity.

Our convergence results generally conform to the results in the existing literature. Some new results do emerge regarding our tests for convergence of total factor productivity. First, we discover stronger evidence of convergence for total factor productivity than for real GDP per capita, suggesting that technological convergence is an important phenomenon. Second, we find strong evidence of convergence of total factor productivity for low- and middle-income countries, and weak evidence of convergence for high-income countries. These findings support the view that

technological change is a public and not a private good. New technological innovations cross country borders, facilitating the convergence of total factor productivity.

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Table 1: Production Function Estimates

	$\ln y$	$\ln y$	$\ln y$	$\ln y$
$\ln k$	0.4756* (18.86)	0.4712* (18.64)	0.3951* (9.38)	0.4751* (18.81)
$\ln L$	-0.0988‡‡ (-1.32)	-0.1383‡ (-1.78)	-0.1988** (-2.39)	-0.1510‡‡ (-1.40)
$\ln h$		0.1136‡ (1.81)		
$\ln H \ln k$			0.0091** (2.38)	
$\ln H \ln L$				0.0025 (0.67)
$time_1$	-0.1097* (-3.99)	-0.1005* (-3.55)	-0.0936* (-3.25)	-0.1071* (-3.80)
$time_2$	-0.0339‡ (-1.66)	-0.0268‡‡ (-1.30)	-0.0224 (-1.08)	-0.321‡‡ (-1.56)
$time_3$	0.0316** (2.13)	0.0360** (2.40)	0.0379** (2.53)	0.0326** (2.19)
$time_4$	0.0426* (3.04)	0.0456* (3.01)	0.0441* (2.91)	0.0460* (3.03)
$time_5$	0.0330‡‡ (1.60)	0.0263 (1.26)	0.0215 (1.02)	0.0312‡‡ (1.50)
$time_6$	0.0328 (1.23)	0.0195 (0.71)	0.0125 (0.45)	0.0293 (1.08)
R^2	0.7860	0.7872	0.7885	0.7857
SEE	0.1269	0.1266	0.1262	0.1270

Note: All regressions employ the fixed-effect technique. Each variable is measured as a deviation from its mean over time, except the 6 time dummy variables (i.e., $time_i$, $i = 1, 2, \dots, 6$) that capture the fixed effects over time. The variables are defined as follows: y equals real GDP per worker; k equals the capital stock per worker; L equals the stock of workers; H equals the stock of human capital; and h equals the stock of human capital per worker. See the Data Appendix for more details about the definitions and sources of data. R^2 is the adjusted coefficient of determination and SEE is the standard error of estimation.

* means significant at the 1-percent level.

** means significant at the 5-percent level.

‡ means significant at the 10-percent level.

‡‡ means significant at the 20-percent level.

Table 2: Real Per Capita GDP and Total Factor Productivity Convergence

	All Countries (83)	Low- Income (22)	Middle- Income (38)	High- Income (23)
<u><i>b-Convergence: Single Cross-Section:</i></u>				
b_y	-0.0005 (-0.26) [81]	-0.0045 (-0.43) [20]	-0.0056 (-0.61) [36]	-0.0184** (-2.74) [21]
b_{tfp}	-0.0084* (-3.29) [81]	-0.0087†† (-1.68) [20]	-0.0114† (-1.96) [36]	-0.0212* (-4.40) [21]
<u><i>b-Convergence: Panel Data:</i></u>				
b_y	-0.0349* (-4.55) [326]	-0.0220†† (-1.49) [82]	-0.0375* (-3.24) [146]	-0.0517* (-3.03) [86]
b_{tfp}	-0.0573* (-6.47) [326]	-0.0615* (-3.39) [82]	-0.0572* (-4.36) [146]	-0.0296†† (-1.65) [86]
<u><i>s-Convergence:</i></u>				
s_y				
(1960-64)	0.8969	0.4455	0.2934	0.2737
(1965-69)	0.9005	0.4326	0.3038	0.2369
(1970-74)	0.9128	0.4400	0.3414	0.1844
(1975-79)	0.9253	0.4879	0.3446	0.1702
(1980-84)	0.9289	0.5415	0.4073	0.2055
(1985-89)	0.9724	0.6476	0.4752	0.2567
(1960-89)	0.9386	0.5217	0.4267	0.2793
s_{tfp}				
(1960-64)	0.4446	0.4968	0.3009	0.2957
(1965-69)	0.4342	0.4689	0.2997	0.2866
(1970-74)	0.4281	0.4359	0.3063	0.2580
(1975-79)	0.4291	0.4396	0.3115	0.2446
(1980-84)	0.4251	0.4769	0.3175	0.2174
(1985-89)	0.4342	0.4834	0.3394	0.2124
(1960-89)	0.4340	0.4597	0.3198	0.2532

Table 2: (continued)

Note: See Table 1. The *bs* come from estimating equation (12) and the *ss* are the standard deviation of real GDP per worker (*y*) and total factor productivity (*tfp*) as measured by the production function that excludes our measure of human capital.

- * means significant at the 1-percent level.
- ** means significant at the 5-percent level.
- ‡ means significant at the 10-percent level.
- ‡‡ means significant at the 20-percent level.

Table 3: Total Factor Productivity Regressions

	<i>ln tfp</i>		<i>ln tfph</i>	
<i>ln H</i>	0.0090 (0.29)	-0.0961†† (-1.64)	-0.0437†† (-1.39)	-0.1357* (-2.32)
<i>ln x</i>	0.1237* (6.08)	0.0925* (3.70)	0.1207* (5.97)	0.0935* (3.76)
<i>ln H ln x</i>		0.0395** (2.12)		0.0346† (1.87)
<i>ln tot</i>	0.0283†† (1.38)	0.0286†† (1.40)	0.0295†† (1.45)	0.0298†† (1.46)
<i>ln pd</i>	-0.0703** (-2.03)	-0.0680** (-2.00)	-0.0779** (-2.26)	-0.0882** (-2.54)
<i>ln (1 + p)</i>	-0.1550* (-3.78)	-0.1560* (-3.82)	-0.1548* (-3.79)	-0.1557* (-3.83)
<i>s_x</i>	-0.0023* (-3.14)	-0.0028* (-3.65)	-0.0024* (-3.20)	-0.0028* (-3.63)
<i>s_{tot}</i>	0.00003 (0.23)	0.00004 (0.30)	0.00003 (0.21)	0.00004 (0.27)
<i>s_{pd}</i>	0.0006†† (1.60)	0.0006† (1.66)	0.0006† (1.68)	0.0008** (1.97)
<i>s_p</i>	0.0116†† (1.33)	0.0117†† (1.35)	0.0115†† (1.33)	0.0116†† (1.34)
<i>time₁</i>	-0.1061* (-6.36)	-0.0955* (-5.74)	-0.1123* (-6.78)	-0.1071* (-6.39)
<i>time₂</i>	-0.0336** (-2.27)	-0.0265† (-1.76)	-0.0369** (-2.45)	-0.0340** (-2.25)
<i>time₃</i>	0.0306** (2.27)	0.0340** (2.54)	0.0302** (2.26)	0.0315** (2.37)
<i>time₄</i>	0.0515* (3.61)	0.0490* (3.45)	0.0548* (3.86)	0.0594* (3.84)
<i>time₅</i>	0.0312** (2.06)	0.0239†† (1.58)	0.0348** (2.31)	0.0312** (2.05)
<i>time₆</i>	0.0264†† (1.53)	0.0152 (0.88)	0.0295† (1.71)	0.0240†† (1.38)
<i>R²</i>	0.3040	0.3071	0.2836	0.2880
<i>SEE</i>	0.1166	0.1163	0.1159	0.1156

Table 3: (continued)

Note: See Table 1. Results of estimating equation (13) where the dependent variables are, in turn, the natural logarithm of total factor productivity derived from production functions that exclude (*tfp*) and include (*tfph*) human capital. Other variables are defined as follows: *x* equals the ratio of exports to GDP; *tot* equals the terms of trade; *pd* equals the local price deviation from purchasing power parity; *p* equals the inflation rate; and s_i equals the standard deviation of $i = x, tot, pd$, and *p* over each 5-year sub-period.

* means significant at the 1-percent level.

** means significant at the 5-percent level.

‡ means significant at the 10-percent level.

‡‡ means significant at the 20-percent level.

Data Appendix:

As noted in the text, the panel data set includes information from 83 countries over the 1960 to 1989 period. Observations are generally averaged over five year sub-periods -- 1960-64, 1965-69, 1970-74, 1975-79, 1980-84, and 1985-89. Thus, the panel includes 498 observations (83 countries and 6 time periods). The countries included in the sample were restricted merely by data availability. Table A lists the countries ranked by their total factor productivity calculated from the production function that excludes human capital. The Table also lists the ranking of the countries based on the total factor productivity estimated when human capital was included in the production function. The rest of this Data Appendix provides more information about the sources and in some cases estimation of the data.

Physical Capital

Most data on the physical capital stock comes from the Penn World Table 5.6 (PWT5.6). Data for some countries in some years were missing from this table. To maintain a reasonably large sample, we estimate the capital stock series for some countries, where either the data on important components of the capital stock are available, or where data on the total capital stock are available for some years. We considered the following procedures in estimating the capital stock series.

1. For those countries that do not have capital stock data available for the beginning of the sample, we choose the steady-state method to estimate missing values. At the steady state, the capital output ratio (K/Y) is constant. This implies that the rates of change in capital and output are equal. Furthermore,

$$dK_t = I_t - \delta K_t, \quad \text{and} \quad (dK_t/K_t) (K_t/Y_t) = (I_t/Y_t) - (\delta K_t/Y_t).$$

Since the steady state levels of output and capital grow at the same rate, we have the following:

$$(dY_t/Y_t) (K_t/Y_t) = (I_t/Y_t) - (\delta K_t/Y_t) \quad \text{and} \quad (g_t + \delta) (K_t/Y_t) = (I_t/Y_t).$$

Thus, solving for the steady-state capital output ratio gives the following:

$$(K_t/Y_t)^* = (I_t/Y_t)^*/(g_t^* + d),$$

where "*" refers to steady-state values and d equals 7 percent.

The steady-state growth rate of output (g^*) does not equal the actual growth rate for any country. Rather, as assumed by King and Levine (1994), we use the following relationship:

$$g^* = I g + (1 - I) g_W,$$

where g is the period-average actual growth rate for the country in question, g_W is the actual world growth rate estimated at 4 percent per year, and $I = 0.25$, a measure of mean reversion in the growth rates, following Easterly et al. (1993). This, then produces the steady-state capital output ratio $[(K_t/Y_t)^*]$.

Finally, multiplying the steady-state capital output ratio by the average output for the five-year period yields the average capital stock for the period, and dividing by the average number of workers for the same period produces the per worker capital stock.

2. When the capital stock in the initial years is available, we follow the perpetual inventory method to calculate the capital stock as follows:

$$K_t = I_t + (1 - d) K_{t-1}.$$

Finally, the estimated numbers are adjusted based on any discrepancy, in the first year the actual numbers are again available, between the estimated and actual numbers.

Human Capital

We employ the average educational attainment (years of schooling) for the adult population, available from the NBER/Barro-Lee (1994) data set.

Terms of Trade

Our main source for export and import prices (and unit values) is *International Financial Statistics* (CD-ROM, July 1996, and several yearbook print issues). Various sources are used to compile the trade price data that are missing from the *International*

Financial Statistics (various issues). Some come from the World Bank *World Tables* (various issues). The remaining data are compiled, and in some cases estimated based on information, from United Nations *Monthly Bulletin of Statistics* (various issues), *International Financial Statistics Yearbook* (various issues), *Direction of Trade Statistics Yearbook* (various issues), and UNCTAD *Handbook of International Trade and Development*, (1994).

Many of the estimated numbers resulted from the use of proxies such as unit values of the commodities or commodity groups that contribute a major share of trade (e.g., export price of phosphate for Jordan, crude petroleum price for Algeria, and cotton and coffee prices for Nicaragua); share-weighted average of major trading partner's import prices (for export prices of the country in question); and export prices (for import prices) where a county's commodity trade is significantly diversified but trade is largely concentrated with a small number of countries (e.g., France's import and export prices proxy Niger's export and import prices for 1959-66, and for the same period for Trinidad & Tobago the import prices are the import-share-weighted average of wholesale prices of the United States and the United Kingdom, and export prices of Venezuela).

Inflation

The chief source of data on inflation is the database for Fischer's World Bank growth project, contained in the World Bank Growth Database. Inflation rates are annual percentage changes in the consumer price index. We added the data for 1960 and 1989 from the *International Financial Statistics* (various issues). For Guinea-Bissau (1960-87), we use, for lack of better data, the average inflation for Africa; and for Jordan (1960-67), the average inflation for "Other Middle East." Both of these series come from the *International Financial Statistics Yearbook* (various issues). Finally, for seven other countries for a few years, we used the GDP deflators, again from the *International Financial Statistics Yearbook* (various issues).

Local Price Deviation from Purchasing Power Parity

This variable comes from the PWT5.6. The variable P in PWT5.6 measures the local price of an identical basket of goods for all countries relative to the price in the United States. Hence it is a measure of the local price deviation from purchasing power parity, with the United States as the reference country.

Openness

We use two measures of openness -- the ratio of exports plus imports to GDP and the ratio of exports to GDP. If exports and imports always move closely together, then the two measures may provide the same information. Levine and Renelt (1992) indicate that these two measures provide the same qualitative results in their analysis of the determinants of growth. We find that exports to GDP performs uniformly better in our analysis of the determinants of total factor productivity.

The data for exports plus imports to GDP come from the PWT5.6. This data base, however, does not separate exports from imports. Hence, to generate exports to GDP, we use *International Financial Statistics Yearbooks* (various issues) for both exports and GDP. To fill in some missing export data for some countries in a few years, we use the *Direction of Trade Statistics* (various issues), the United Nations *Monthly Bulletin of Statistics* (various issues), and the UNCTAD *Handbook of International Trade and Development* (1994).

Volatility Measures

We use volatility measures of (1) inflation, (2) terms of trade, (3) local price deviation from purchasing power parity, (4) exports-plus-imports-to-GDP ratio, and (5) export-to-GDP ratio. We measure volatility as the standard deviation of a variable for the 5 years that constitute the respective 5-year period in the sample.

Table A

Country	Rank <i>tfp</i>	Rank <i>tfph</i>	Country	Rank <i>tfp</i>	Rank <i>tfph</i>
United States	1	1	Hong Kong	43	45
Trinidad-Tobago	2	7	Mauritius	44	49
United Kingdom	3	3	Fiji	45	57
France	4	4	Israel	46	55
Bangladesh	5	2	Uganda	47	39
Jordan	6	12	Greece	48	51
Venezuela	7	9	Haiti	49	42
Netherlands	8	13	Turkey	50	41
Argentina	9	11	Syria	51	50
Canada	10	14	Portugal	52	46
Algeria	11	8	South Korea	53	53
Brazil	12	5	Malta	54	63
Iran	13	6	Senegal	55	52
Australia	14	18	Paraguay	56	61
Mexico	15	10	India	57	38
West Germany	16	16	Iceland	58	64
Italy	17	15	Dominican Republic	59	59
New Zealand	18	28	Thailand	60	54
Belgium	19	24	Ghana	61	56
Japan	20	17	Colombia	62	58
Austria	21	22	Philippines	63	60
Sweden	22	27	Peru	64	62
South Africa	23	20	Cyprus	65	66
Uruguay	24	30	Ecuador	66	65
Yugoslavia	25	26	Swaziland	67	69
Spain	26	23	Bolivia	68	67
El Salvador	27	29	Jamaica	69	70
Mozambique	28	19	Panama	70	72
Tunisia	29	25	Botswana	71	71
Denmark	30	36	Papua New Guinea	72	68
Pakistan	31	21	Honduras	73	73
Nicaragua	32	33	Guyana	74	77
Guatemala	33	32	Zambia	75	74
Barbados	34	48	Lesotho	76	78
Chile	35	37	Sri Lanka	77	76
Malaysia	36	34	Malawi	78	75
Singapore	37	40	Kenya	79	79
Ireland	38	43	Niger	80	80
Indonesia	39	31	Togo	81	81
Norway	40	44	Zimbabwe	82	82
Finland	41	47	Guinea-Bissau	83	83
Zaire	42	35			

Table A: (continued)

Note: The countries are ranked based on the logarithm of total factor productivity calculated from the production function specifications that exclude (*tfp*) and include (*tfp_h*) our measure of human capital. The actual values of the logarithm of total factor productivity are available on request.